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Controlling and Monitoring Milk Pasteurization using Fuzzy Logic integrated with the Internet of Things (IoT)

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***Abstract*— Precise temperature control in nonlinear thermal processes with fluctuating conditions remains a challenge for traditional control methods. This research presents a Mamdani-type fuzzy logic control system integrated with an IoT architecture for milk pasteurization using the Low-Temperature Long-Time (LTLT) method, which is widely used in Indonesia for small-scale dairy production. The controller takes milk temperature and volume as linguistic inputs and outputs a continuous PWM signal to regulate heater power. Unlike traditional on–off systems or model-based PID controllers, this fuzzy logic approach does not rely on an explicit mathematical model and remains effective across different milk volumes without retuning. Experiments with 3 L, 5 L, and 8 L of milk show that the controller keeps temperatures close to the 64°C target, with averages of 64.11°C, 64.07°C, and 64.03°C, respectively. Max overshoot is limited to 1.56%, 0.29%, and 0.19%, while high-temperature stability is demonstrated by standard deviations of 0.26, 0.08, and 0.12, indicating robustness. Furthermore, it functions at a lower average PWM duty cycle compared to on–off control, leading to smoother operation and improved efficiency. This system can handle nonlinear thermal processes with varying loads and is supported by real-time IoT connectivity monitoring.**

Index Terms— ***Fuzzy logic control; Mamdani inference system; Milk pasteurization; Low-temperature long-time (LTLT); Internet of Things (IoT)***

I. INTRODUCTION

Milk is a vital source of protein, an essential component of feed formulations for both children and adults. During processing to become consumed milk, raw milk is pasteurized. This is because pasteurization creates an ideal environment that prevents rapid growth of harmful microorganisms, especially when stored at or below room temperature. Pasteurization is a method developed by the French scientist Louis Pasteur in the 1800s. The process, which involves heating milk to a high temperature and then rapidly cooling it, extends its shelf life, a process known as Extending Shelf Life (ESL) [1]. Milk pasteurization primarily aims to eliminate harmful bacteria and reduce spoilage bacteria, thereby extending milk shelf life. Therefore, pasteurization is a crucial step in milk processing, ensuring microbial control and preserving food quality for consumers by removing pathogens that cause disease, preventing souring, and maintaining nutrient quality. There are various methods for pasteurizing milk, which can be categorized into two groups: traditional and modern methods [1]. Traditional methods included thermal pasteurization, such as low-temperature short-time (LTST), low-temperature long-time (LTLT), high-temperature short-time (HTST), and flash pasteurization, all of which use temperatures below the boiling point. Then modern methods include high-temperature (HT) and UHF pasteurization [2], [3], [4].

Among those pasteurization methods, high-temperature short-time (HTST) and low-temperature long-time (LTLT) pasteurization are the most widely used. In Indonesia, a survey indicates that the cattle-farming community and milk processing industry still rely on a slow-heating method to enhance milk flavor. As a result, LTLT pasteurization is deemed suitable for Indonesia's milk industry, as it promotes effective blending of milk and its flavor [5]. LTLT is the process of pasteurizing milk by heating it to 65°C and holding it at that temperature for 30 minutes [6]. Maintaining the exact temperature is vital in the LTLT pasteurization method because achieving that temperature enables inactivation of non-spore-forming pathogens, such as psychrotrophic spoilage bacteria, including Gram-negative Pseudomonas [4], and Coxiella burnetii, the most heat-resistant pathogen in raw milk [6]. Additionally, LTLT showed no significant changes in nutrient levels, except for a slight loss of Vitamin A and Vitamin C. This type of milk can be stored for up to 2-3 days before spoilage due to putrefactive organisms rather than acid formation [7].

Several control system approaches have been developed to optimize milk pasteurization outcomes in prior research, including model predictive control [8], Proportional-Integral-Derivative (PID) control [3], and artificial intelligence Internet of Things (AIoT) approaches [8]. However, those methods have several limitations. The model predictive control method faces inherent challenges, including noisy signals, model accuracy issues, and hardware constraints. Then, the PID approach requires tuning of several parameters, including proportional (P), integral (I), and derivative (D), which are appropriate for a given volume. Fixed PID gains are inadequate when process conditions change significantly, such as when a volume change happens [9]. Subsequently, the AIoT approach proved inefficient for higher-capacity applications, as it required more time to reach the setpoint [8]. Therefore, this study employs an alternative approach: fuzzy logic, which is more efficient for larger volumes when reaching the setpoint temperature. Fuzzy logic control was also used in the previous study; however, in that study, the controller was a PLC, which is well-suited to industrial production processes. In this study, the controller is an ESP32, which is more appropriate for the cattle-farming community. Several fuzzy logic algorithms exist, such as Mamdani-type, Sugeno-type, and Tsukamoto-type [10], [11]. However, this study uses Mamdani-type fuzzy logic because it provides high interpretability and clear linguistic transparency. In contrast, Sugeno-type fuzzy logic relies on mathematical functions in its consequents, which are harder to interpret [11]. Mamdani is better suited to ill-defined nonlinear systems than Tsukamoto, which requires monotonic functions and crisp outputs for each rule, thereby limiting flexibility for complex nonlinear behavior. Mamdani systems also offer a richer representation of uncertainty than Sugeno systems, which directly convert outputs into crisp values—this can improve computational efficiency but reduces explicit uncertainty representation. Additionally, Mamdani is often the preferred choice when introducing fuzzy logic or when ease of acceptance among operators and engineers is essential, as its control architecture is straightforward, which covers fuzzification, inference, aggregation, and defuzzification [11].

The earlier pasteurization system that employed fuzzy logic [17] did not account for the efficiency of the power heater used to warm the milk. To address this in the current study, specific parameters—milk temperature and milk volume—have been selected as inputs for the fuzzy logic controller. This approach aims to optimize the power heater's efficiency while ensuring the milk reaches the standard temperature required by the LTLT process. According to the references, IoT systems facilitate real-time monitoring and control of essential process parameters in dairy processing, such as milk pasteurization. This integration can greatly improve operational efficiency, product quality, and safety [16]. In this study, the IoT system is employed to oversee the LTLT process and track real-time physical parameters of milk, ensuring that the standard LTLT temperature is achieved while preserving heater efficiency. The monitoring and control dashboard on the PC display is used to communicate with the ESP32 microcontroller via TCP/IP over Wi-Fi within a local area network.

II. Methods

Fuzzy logic is a mathematical framework for managing uncertainty and vagueness, making it helpful in solving complex problems in engineering, artificial intelligence, and decision-making [12]. Fuzzy logic enables modeling a system using fuzzy sets and rules that describe its behavior. Three common methods of deductive inference in fuzzy systems that rely on linguistic rules are (1) Mamdani systems, (2) Sugeno models, and (3) Tsukamoto models [11], [13]. In fuzzy logic, truth values range from entirely true to completely false. The completely true value is explicitly 1, while the completely false value is explicitly 0 [13]. In Fuzzy Logic, instead of simply giving a yes or no answer, the truth value or membership indicates a matter of degree. The Mamdani method was first introduced by Ebrahim Mamdani in 1975. It is among the most popular fuzzy inference techniques because its results are both visualizable and linguistically understandable. In this approach, each fuzzy rule has an antecedent (IF) and a consequent (THEN). The inference process employs the min operator to assess the truth degree in the antecedent and the max operator to combine the results in the consequent. Generally, the Mamdani-type fuzzy logic method consists of a fuzzifier, a fuzzy inference module containing rules, and a defuzzifier. The steps of the fuzzy logic method are shown in Fig.1.

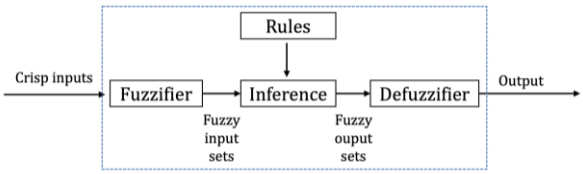

Fig. 1. The Fuzzy Logic Step of the Mamdani-type

The fuzzy logic control method implemented in this system is based on a Mamdani fuzzy inference system, which comprises three main stages: fuzzification, inference using fuzzy rules, and defuzzification. This controller regulates heater power to maintain milk temperature at 63–65 °C for 30 minutes, in accordance with the LTLT pasteurization method. The first step of the Mamdani fuzzy system is fuzzification. Fuzzification is the process of converting crisp input values into fuzzy values using membership functions. In this system, two input variables (milk volume and temperature parameters) and one output variable (heater power percentage) are defined. The milk volume input is obtained from the ultrasonic sensor HY-SRF05, and the temperature data is collected from the DS18B20 sensor. The milk tank has a capacity of 10 liters. The milk used in this study is from cattle farmers and was purchased for this project. Then, the physical parameters of milk, which are temperature and the milk volume, are used as the input parameters of the membership function of fuzzy. Triangular or trapezoidal membership functions are used to represent each input variable. The triangular membership function is defined as shown in Equation 1, where a triangular fuzzy set is characterized by the parameters a, b, and c. While μ(x) is a fuzzy degree (μ ϵ [0,1]). Equation 1 is used when the membership function has a single peak [13].

$$\mu(x) = \begin{cases} 0, & x \leq a \text{ or } x \geq c \\ \frac{x-a}{b-a}, & a < x < b \\ \frac{c-x}{c-b}, & b < x < c \end{cases} \quad (1)$$

For a trapezoidal fuzzy set with parameters a, b, c, and d, the membership function is given as shown in Equation 2 [13]. Equation 2 is used to represent stable operating regions, such as the desired temperature range (63 – 65) °C).

$$\mu(x) = \begin{cases} 0, & x \leq a \text{ or } x \geq d \\ \frac{x-a}{b-a}, & a < x < b \\ 1, & b < x < c \\ \frac{d-x}{d-c}, & c < x < d \end{cases} \quad (2)$$

Fuzzification involves creating a fuzzy set through membership functions. The input variable classifications, including milk volume and temperature, are listed in Table I. The justification for determining the membership function range in Table I is based on expert knowledge, ensuring that the LTLT process can be operated at the standard temperature of 65 °C while maintaining the heater's efficiency.

TABLE I. MEMBERSHIP CLASSIFICATION

Input Variable Classifications			
Temperature parameters	**Temperature Range (°C)**	**Milk Volume**	**Milk Volume Range (%)**
Cold	-6 – 20	Empty	0 - 20
Normal	18 – 64	Low	20 – 45
Warm	63.5 – 65.5	Medium	45 – 70
Hot	65 – 80	Full	65 - 100

In Table I, the Cold parameters indicate the initial raw milk conditions before heating. The Normal parameters indicate the temperature at which the milk begins to warm toward the target pasteurization temperature. Warm parameters show when the milk is adequately heated and nearing the ideal temperature. Lastly, Hot parameters indicate that the milk has reached or exceeded the pasteurization temperature, requiring controlled heating to maintain a steady temperature and avoid overheating. The graphical display of both membership functions is shown in Fig. 2.

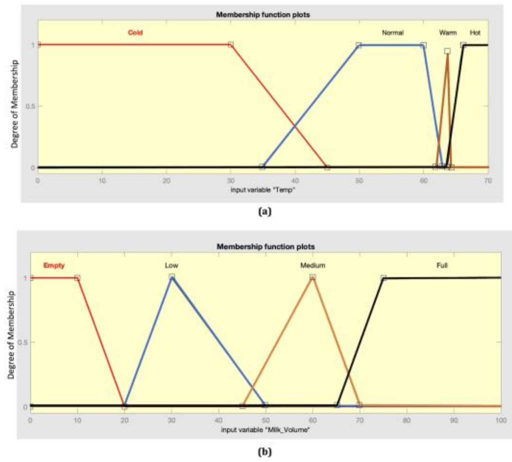

Fig. 2. The graphical display of the membership function for (a) the temperature input and (b) the milk volume input (small box indicates the parameter point)

If the fuzzy inference system has numerous input variables, meaning the rule antecedents have many components, then fuzzy logic operators are used to combine the membership values and produce a single outcome that reflects the rule's result. The if-then rules are generated based on the membership values of each fuzzy set within the input variables [13], [14]. The general fuzzy rule is expressed as shown in Equation 3.

$$IF\ (T\ is\ A_i)\ AND\ (L\ is\ B_j)\ THEN\ (P\ is\ C_k) \quad (3)$$

A_i and B_j denote fuzzy sets of temperature and milk volume, respectively, and C_k denotes a fuzzy set of heater power. The degree of activation (firing strength) of each rule is calculated using the minimum operator, as shown in Equation 4 [11], [13].

$$\alpha_r = \min\left(\mu_{A_i}(T), \mu_{B_j}(L)\right) \quad (4)$$

Where α_r is the firing strength of rule r, $\mu_{A_i}(T)$ is the membership degree of temperature, and $\mu_{B_j}(T)$ is the membership degree of milk volume. Next, the outputs of all activated rules are combined using the maximum (max) operator, as shown in Equation 5. This aggregated fuzzy set represents the final fuzzy output before defuzzification [11], [13].

$$\mu_{output}(z) = \max(\alpha_1, \alpha_2, \cdots, \alpha_n) \quad (5)$$

The fuzzy logic rule used in this study is presented in Table II.

TABLE II. THE RULE OF FUZZY LOGIC IN THIS STUDY

No.	Input Variable Classifications		
	Temperature parameters	**Milk Volume**	**Output**
1	Hot	Empty	Level 0
2	Hot	Low	Level 0
3	Hot	Medium	Level 0

No.	Input Variable Classifications		
	Temperature parameters	Milk Volume	Output
4	Hot	Full	Level 0
5	Warm	Empty	Level 0
6	Warm	Low	Level 1
7	Warm	Medium	Level 1
8	Warm	Full	Level 1
9	Normal	Empty	Level 0
10	Normal	Low	Level 2
11	Normal	Medium	Level 3
12	Normal	Full	Level 3
13	Cold	Empty	Level 0
14	Cold	Low	Level 2
15	Cold	Medium	Level 2
16	Cold	Full	Level 2

Description: Output represents the percentage of the heater power, which can be described as follows: Level 0: 0%, Level 1: 20 – 45%, Level 2: 50 – 70%, Level 3: 85 – 100%

The output of the fuzzy logic controller is heater power, expressed as a Pulse Width Modulation (PWM) signal. The output fuzzy sets (Level 0, Level 1, Level 2, and Level 3) represent the percentage of the PWM duty cycle associated with the heater power condition.

The last step of Mamdani fuzzy logic implementation is defuzzification. Defuzzification converts the aggregated fuzzy output into a crisp numerical value. Several defuzzification methods can be used, including Bisector of Area (BOA), Center of Area (COA), Mean of Maximum (MOM), Smallest of Maximum (SOM), and Largest of Maximum (LOM) [13], [15]. In this study, the COA method was used for defuzzification. The general equation of the COA method is shown in Equation 6

$$z_{COA} = \frac{\int_z \mu_A(z)\cdot z\,dz}{\int_z \mu_A(z)dz} \quad (6)$$

Where Z_{COA} is crisp output, $\mu_A(z)$ is the membership function of the aggregated output z.

$$z_{trapezoid} = \frac{a+2b+2c+d}{6}, \quad (7)$$

$$z_{triangle} = \frac{a+b+c}{3}. \quad (8)$$

The crisp value Z obtained from defuzzification is then converted into a PWM duty cycle, which is applied to the AC Light Dimmer to control the heater power. This process is repeated continuously in real time to ensure stable temperature control during pasteurization. The process has been monitored using an IoT system, which is connected to the hardware via TCP/IP over Wi-Fi within a local area network. Fig. 3 shows the 3D model of the hardware system. Then the monitoring system is shown in Fig. 4. Then, The overall steps are illustrated in the flowchart in Fig. 5.

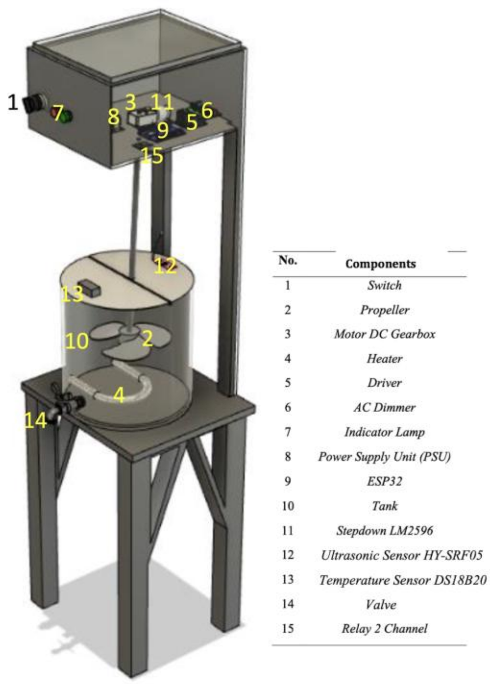

Fig. 3. The 3D design of the system

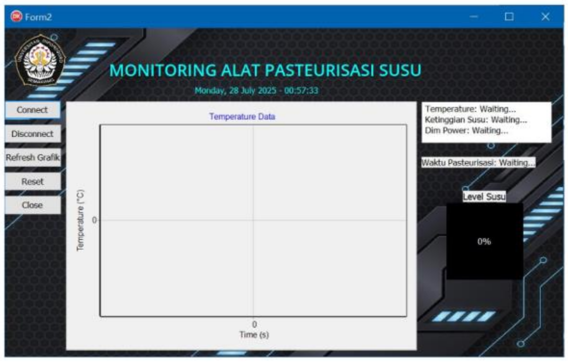

Fig. 4. The Flowchart of the system

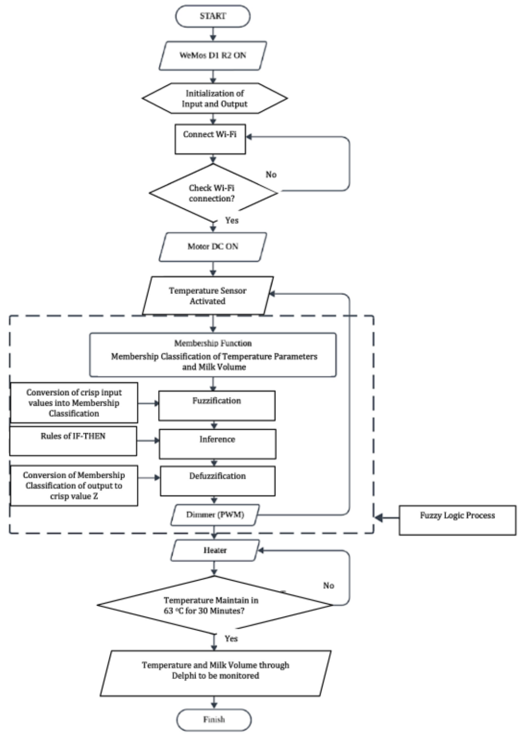

Fig. 5. The monitoring dashboard of the system

The block diagram of the proposed pasteurization system is presented in Fig. 6. Fig. 6(a) presents the hardware and IoT system, while Fig. 6(b) shows how the milk, fuzzy logic, and IoT components interact within this framework. The communication of the IoT components in this study uses TCP/IP over Wi-Fi within a local area network.

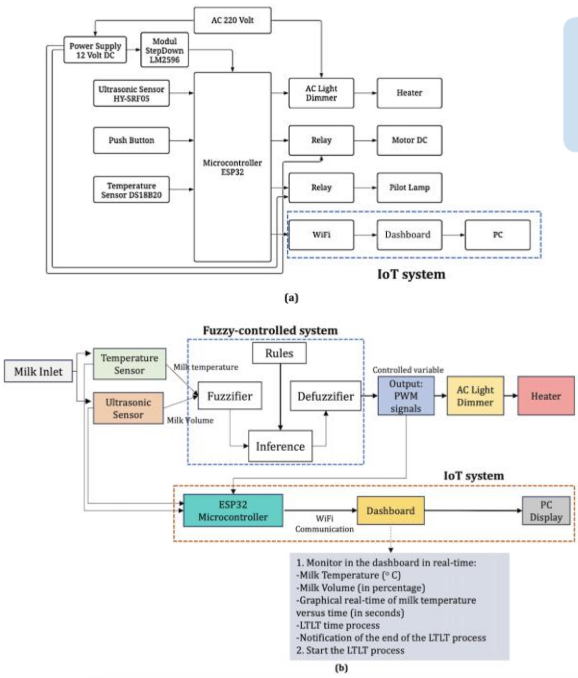

Fig. 6. The block diagram of the proposed pasteurization system, including (a) the block diagram of hardware and IoT system, and (b) the block diagram of the interaction among the milk, fuzzy logic, and IoT components within this framework

III. RESULTS AND DISCUSSION

This study tests the membership results using three milk-volume categories: 3 liters, 5 liters, and 8 liters. The 3-liter category indicates low milk volume, 5 liters represents medium volume, and 8 liters signifies full volume. A case-scenario approach to fuzzy set membership was used to optimize the membership function, which was subsequently analyzed. The case-scenario process for fuzzy set membership is presented in Table III. The results of the case-scenario in Table III are shown in Fig. 7 for milk volumes of 3 liters, 5 liters, and 8 liters.

TABLE III. THE CASE-SCENARIO MEMBERSHIP OF FUZZY LOGIC IN THIS STUDY

No.	Trials	Temperature Parameters (°C)	Membership in Temperature Parameters Fuzzy Set	Milk Volume (Liters)	Membership in Milk Volume Fuzzy Set	Output Parameters	Membership in Output Parameters
1.	Case Scenario 1	Cold	(-6, 0, 10, 20)	Empty	(0, 0, 10, 20)	Level 0	(0, 0, 0, 0)
		Normal	(18, 30, 45, 64)	Low	(20, 30, 30, 45)	Level 1	(10, 25, 40, 60)
		Warm	(63.5, 64, 64, 65.5)	Medium	(45, 50, 50, 70)	Level 2	(60, 70, 80, 90)
		Hot	(65, 66, 75, 80)	Full	(65, 75, 100, 100)	Level 3	(90, 100, 100, 100)
2.	Case Scenario 2	Cold	(-6, 0, 10, 20)	Empty	(0, 0, 10, 20)	Level 0	(0, 0, 0, 0)
		Normal	(18, 30, 45, 63.56)	Low	(20, 30, 30, 45)	Level 1	(30, 40, 40, 50)
		Warm	(63, 63.69, 63.69, 64.5)	Medium	(45, 50, 50, 70)	Level 2	(60, 70, 80, 90)
		Hot	(64, 66, 75, 80)	Full	(65, 75, 100, 100)	Level 3	(90, 100, 100, 100)
3.	Case Scenario 3 (Final)	Cold	(-6, 0, 20, 45)	Empty	(0, 0, 10, 20)	Level 0	(0, 0, 0, 0)
		Normal	(35, 50, 50, 63)	Low	(20, 30, 30, 50)	Level 1	(30, 40, 40, 50)
		Warm	(62, 63.94, 63.94, 64.06)	Medium	(45, 60, 60, 70)	Level 2	(50, 60, 60, 70)
		Hot	(63.69, 66, 75, 80)	Full	(65, 75, 100, 100)	Level 3	(85, 90, 95, 100)

The results of the case-scenario in Table III are shown in Fig. 7 for milk volumes of 3 liters, 5 liters, and 8 liters. The comparison results show that the best membership parameters come from case scenario 3 (the Final parameters), as indicated by the blue line. As shown in Fig. 7(a), for a 3-liter milk volume, the average temperature is 64.11°C, with a minimum overshoot of 1.56% and a standard deviation of 0.26. In comparison, Case scenario 1 reaches 65.77°C, with a 4.00% overshoot and a standard deviation of 0.40. Similarly, Case scenario 2 reaches an average temperature of 64.44°C, with a 2.34% overshoot and a standard deviation of 0.37. For a 5-liter milk volume, the comparison results also indicate that the best membership parameters are from Case scenario 3 (the Final parameters), again marked by the blue line. As shown in Fig. 7(b), the average temperature is 64.07°C, with a minimum overshoot of 0.29% and a standard deviation of 0.08. In comparison, Case scenario 1 reaches 65.49°C, with a 3.03% overshoot and a standard deviation of 0.34. Similarly, Case scenario 2 reaches an average temperature of 64.63°C, with a 1.75% overshoot and a standard deviation of 0.20. For an 8-liter milk volume, the comparison results also demonstrate that the best membership parameters are from Case scenario 3 (the Final parameters), as indicated by the blue line.

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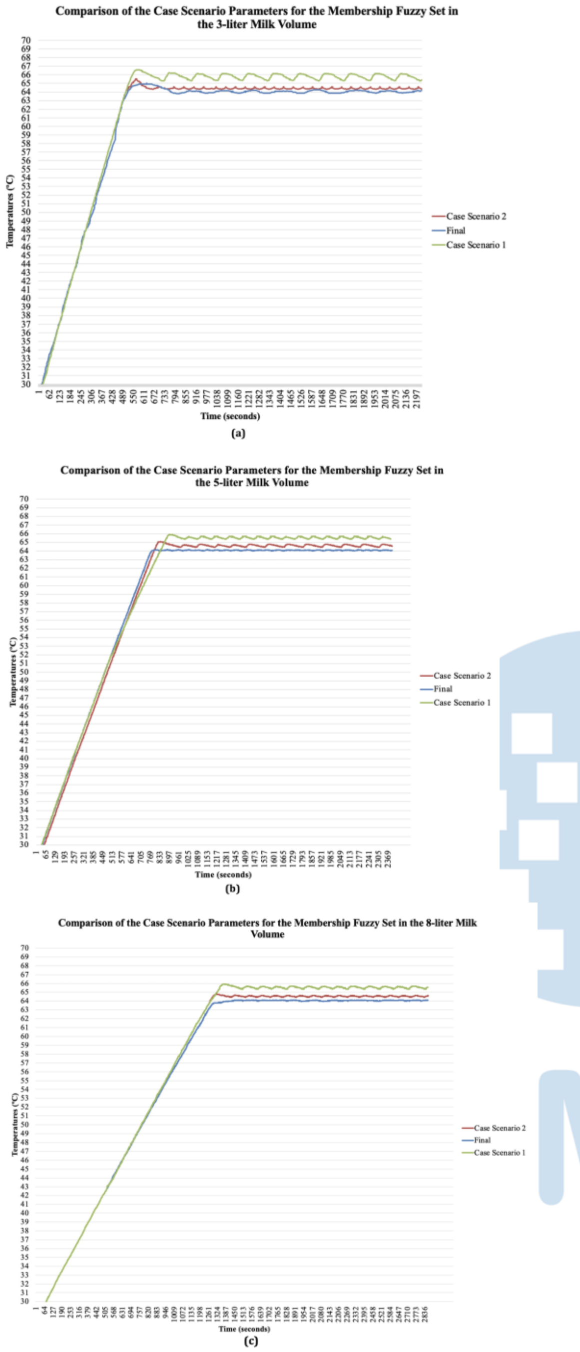

Fig. 7. The comparison result of the case-scenario parameters for the membership fuzzy set in (a) 3-liter milk volume, (b) 5-liter milk volume, and (c) 8-liter milk volume (the red line indicates case sceanrio 1, the blue line indicates case scenario 3 (Final).

As shown in Fig. 7(c), the average temperature is 64.03°C, with a minimum overshoot of 0.19% and a standard deviation of 0.12. In comparison, Case scenario 1 reaches 65.47°C, with a 3.03% overshoot and a standard deviation of 0.37. Similarly, Case scenario 2 reaches an average temperature of 64.52°C, with a 1.27% overshoot and a standard deviation of 0.27. Therefore, the optimal membership values for the fuzzy set parameters are listed in Table IV.

TABLE IV. THE OPTIMUM MEMBERSHIP OF FUZZY SET PARAMETERS

Input Variable Classifications			
Temperature parameters	**Temperature Range (^{o} C)**	**Milk Volume**	**Milk Volume Range (%)**
Cold	-6 – 45	Empty	0 - 20
Normal	35 – 63	Low	20 – 50
Warm	62 – 64.06	Medium	45 – 70
Hot	63.69 – 80	Full	65 - 100

The performance of the Mamdani fuzzy logic control system developed in this study was quantitatively assessed and compared with the traditional on–off control method using several key performance metrics, including average temperature, set-point temperature tracking, temperature overshoot, rise time, standard deviation of temperature, and average PWM output of the AC light dimmer. These metrics were chosen because they directly indicate the effectiveness, stability, and efficiency of the LTLT pasteurization process. The set-point temperature in this study is 64 °C. Testing milk volumes of 3 liters, 5 liters, and 8 liters using a Mamdani fuzzy logic control system demonstrated improved temperature regulation compared with the traditional on-off control method, particularly in reducing overshoot as shown in Table V. The experimental results show that the Mamdani fuzzy logic controller maintains an average operating temperature that closely aligns with the target set-point of 63–65 °C. In various test volumes, the average temperature under fuzzy control remains reliably centered around the desired set-point, indicating effective tracking performance.

In contrast, the on-off control system exhibits a larger difference between the average temperature and the setpoint. Because the control action is binary (either fully ON or fully OFF), the system's temperature fluctuates more significantly around the target, causing the average temperature to drift outside the ideal pasteurization range. This indicates that the on-off controller lacks the resolution needed for precise temperature control in continuous thermal processes. Additionally, Mamdani fuzzy logic requires a lower PWM duty cycle than conventional on-off control, as shown in Table V. A comprehensive comparison of key performance metrics is presented in Table V.

TABLE V. PERFORMANCE OF MAMDANI FUZZY LOGIC WITH OPTIMAL FUZZY SET MEMBERSHIP PARAMETERS

Temperature Control System	Milk Volume (liters)	Key performance metrics					
		Average Temperature During Fuzzy Control (°C)	Set-point Temperature (°C)	Temperature Overshoot (%)	Rise Time (seconds)	Standard Deviation of Temperature	Average PWM Dimmer Duty Cycle During Fuzzy Control (%)
Mamdani Fuzzy Logic (This Study)	3	64.11	64	1.56	180	0.26	23.81
	5	64.07	64	0.29	210	0.08	37.89
	8	64.03	64	0.19	310	0.12	50.15
Traditional on-off control method	3	65.67	64	9.17	-	1.66	27.58
	5	64.28	64	1.56	-	0.45	35.99
	8	64.15	64	1.27	-	0.39	52.54

This study compares the Mamdani fuzzy logic controller to a PID control system [3] used for industrial milk pasteurization. Results indicate that the Mamdani controller is slower than the PID, with rise and settling times of 0.177 and 0.34 seconds, respectively, and no overshoot in ideal simulation conditions at a milk flow rate of 325 L/min [3]. Nonetheless, the Mamdani controller emphasizes long-term temperature stability and robustness amid varying milk volumes, as shown in Table V, without depending on mathematical models.

IV. Conclusion

This study demonstrates that a Mamdani-type fuzzy logic control system, combined with an Internet of Things (IoT) framework, can effectively oversee and regulate the Low-Temperature Long-Time (LTLT) milk pasteurization process. Using milk volume and temperature as input parameters, the proposed fuzzy controller can smoothly adjust heater power and keep the process temperature within the critical range of 63–65 °C for 30 minutes, ensuring microbial safety while maintaining milk quality.

Experimental results with different milk volumes (3 L, 5 L, and 8 L) indicate that the optimized fuzzy membership parameters markedly enhance control performance. The Mamdani fuzzy logic controller achieves temperatures that closely follow the target setpoint while minimizing overshoot and reducing temperature fluctuations, as evidenced by lower standard deviations than traditional on–off control methods. These findings demonstrate that fuzzy logic provides superior stability and accuracy for continuous thermal processes such as LTLT pasteurization. In addition, the fuzzy logic approach requires a lower average PWM duty cycle for the AC light dimmer than the on–off controller, indicating more efficient energy usage and smoother actuator operation. Although the fuzzy controller exhibits slower rise and settling times than PID control reported in prior industrial-scale studies, it offers greater robustness to variations in milk volume. It does not rely on an accurate mathematical model of the process. This makes the proposed system particularly suitable for small-scale, community-based milk-processing applications, such as those commonly found in the Indonesian cattle-farming sector.

Overall, combining Mamdani Fuzzy Logic with IoT-based monitoring provides a practical, stable, and energy-efficient solution for LTLT milk pasteurization. Future efforts could expand the system to achieve higher capacities, incorporate adaptive or hybrid control methods, and evaluate long-term reliability and scalability in real industrial settings.

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